

# INTERCOMPARISON AND SELECTION OF RAINFALL ESTIMATION AND NOWCASTING ALGORITHMS BY THE GOES-R ALGORITHM WORKING GROUP

Robert J. Kuligowski, NOAA/NESDIS Center for Satellite Applications and Research, Camp Springs, MD USA Bob.Kuligowski@noaa.gov

## Background / Objective

### Hydrology Application Team (AT) Background

- Support the AWG by providing recommended, demonstrated, and validated algorithms for processing GOES-R observations into user-required products which satisfy requirements.
- Each Application Team will:
  - Review candidate algorithms and identify algorithm deficiencies;
  - Establish priorities and suggest solutions to resolve deficiencies;
  - Formulate, oversee, and participate in algorithm intercomparisons;
  - Recommend algorithms for GOES-R.
- The selected algorithms will then be demonstrated and documented for delivery to the System Prime via the GOES-R Program Office.

### Hydrology AT Members

- Bob Kuligowski, NESDIS/STAR, Chair
- Ralph Ferraro, NESDIS/STAR
- Kuo-lin Hsu, UC-Irvine
- George Huffman, NASA-GSFC (SSAI)
- John Janowiak, UMCP/ESSIC
- Matthew Sapiano, UMCP/ESSIC

### Hydrology AT Environmental Data Records (EDR's)

- 3.4.6.1, "Probability of Rainfall" (0-3 h)
- 3.4.6.2, "Rainfall Potential" (0-3 h)
- 3.4.6.3, "Rainfall Rate / QPE"

### Objective

- Select algorithms that will form the basis of the Hydrology EDR's in the GOES-R Ground System:
  - Rainfall rate retrieval;
  - Nowcasts of reflectances and brightness temperatures, which will be processed by the rainfall retrieval algorithm to form the basis for the Rainfall Potential and Probability of Rainfall EDR's.

## Candidate Algorithms and Validation Data Sets

### Candidate Nowcasting Algorithms

- Hydro-Nowcaster (HN; Scofield et al. 2004) computes displacement vectors via correlation matching; applies statistically-optimized growth / decay parameters
  - Also a variant (HNsd) that rescales nowcasts to preserve the variance of the initial observations.
- K-Means (Lakshmanan et al. 2003)—uses hierarchical K-means clustering to identify features and motion vectors at multiple scales; simple growth / decay based on temperature changes.
- Thunderstorm Initiation, Tracking, and Nowcasting (TITAN; Dixon and Wiener 1993)—identifies contiguous cloud features and weighted centroids and tracks / extrapolates motion.
  - Also a variant (TITANgd) that extrapolates growth / decay with time.
- McGill Algorithm for Precipitation Nowcasting by Lagrangian Extrapolation (MAPLE; Turner et al. 2004)—uses a variational scheme for echo tracking, wavelet filters to estimate predictability at each scale, and semi-Lagrangian advection.

### Candidate QPE Algorithms

- QMORPH (Joyce et al. 2004a)—extrapolates the most recent MW rain rates forward in time using IR-derived motion vectors.
- CPC-IRFREQ (Joyce et al. 2004b)—matches the cumulative distributions of IR brightness temperatures with MW rainfall rates at 8-km resolution to fill in gaps in MW imagery
- CMORPH—hybrid of QMORPH and CPC-IRFREQ that chooses one or the other based on proximity in space to MW data (closer favors QMORPH; farther away favors CPC-IRFREQ)
- NRL-Blended (Turk et al. 2003)—matches the cumulative distributions of IR brightness temperatures with MW rain rates at the MW footprint resolution.
- PERSIANN (Sorooshian et al. 2000)—uses artificial neural networks to match radiance values and spatial textures with MW rain rates.
- SCaMPR (Kuligowski 2002)—uses discriminant analysis and regression to relate radiance values to MW rain rates.

### Proxy and Ground Validation Data

- METEOSAT Second Generation (MSG) Spinning Enhanced Visible and InfraRed Imager (SEVIRI) data were used as ABI proxy channels
- Rainfall round validation data include:
  - ~16,000 **daily** rain gauges over the SEVIRI full disk obtained from CPC;
  - ~1,125 **daily** gauges and ~65 **hourly** gauges from the British Atmospheric Data Center (BADC) MIDAS data;
  - ~12 **10-min** gauges on floating buoys from the Pilot Research Moored Array in the Atlantic (PIRATA).
- Nowcast validation used the corresponding SEVIRI data as ground truth.

## Methodology and Sample Results

### Candidate Algorithm Evaluation

- Algorithm developers used SEVIRI data from 1-5 January, April, July, and October 2005 to adapt their algorithms for ABI capabilities.
- SEVIRI data from the 6<sup>th</sup> through the 9<sup>th</sup> of each month were used to create independent estimates for evaluation by the Hydrology AT.
- The Hydrology AT evaluated the algorithms against the corresponding gauge (rain rate) or SEVIRI (nowcasts) data over selected regions to reduce data volume.

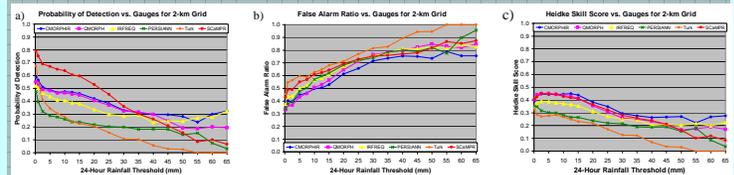


Figure 1. Binary scores: (a) probability of detection; (b) false alarm ratio; and (c) Heidke Skill Score as a function of observed 24-h CPC gauge rainfall accumulation.

a)	RMSE (mm)	Volume Bias	CC	b)	RMSE (mm)	Volume Bias	CC	c)	RMSE (mm)	Volume Bias	CC
CMORPHIR	<b>7.248</b>	<b>0.940</b>	0.559	CMORPHIR	0.838	0.175	0.144	CMORPHIR	1.066	<b>1.039</b>	0.078
QMORPH	7.785	0.938	0.520	QMORPH	0.832	0.152	0.168	QMORPH	1.349	1.771	0.075
CPC-IRFREQ	8.188	0.935	0.481	CPC-IRFREQ	0.852	0.218	0.112	CPC-IRFREQ	0.938	0.718	0.055
PERSIANN	7.728	0.613	0.409	PERSIANN	<b>0.826</b>	0.146	<b>0.174</b>	PERSIANN	<b>0.806</b>	0.204	0.051
NRL-Turk	7.772	0.825	0.351	NRL-Turk	3.130	2.734	0.098	NRL-Turk	1.428	2.045	<b>0.305</b>
SCaMPR	7.506	1.437	<b>0.566</b>	SCaMPR	0.861	<b>0.511</b>	0.136	SCaMPR	0.866	0.837	0.141

Table 1. Rainfall estimates sampled onto a 2-km grid versus (a) 24-h CPC gauges; (b) 1-h MIDAS gauges; (c) 10-min PIRATA gauges. Statistics are Root Mean Squared Error (RMSE), volume bias ratio, and correlation coefficient (CC).

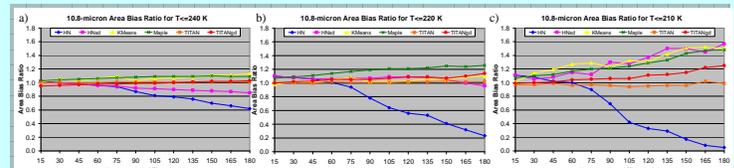


Figure 2. Area bias ratio as a function of nowcast lead time for IR window (10.8-μm) temperatures below (a) 240 K; (b) 220 K; and (c) 210 K.

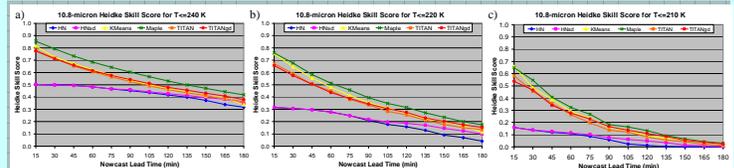


Figure 3. Heidke Skill Score as a function of nowcast lead time for IR window (10.8-μm) brightness temperatures below (a) 240 K; (b) 220 K; and (c) 210 K.

## Conclusions

### Rain Rate

- The CMORPHIR algorithm performed best overall, followed by QMORPH and SCaMPR.
- However, the developers elected not to participate in operational implementation, so SCaMPR will be used in the demonstration GOES-R Ground System.

### Nowcasts

- The MAPLE algorithm performed best overall, followed by K-Means and TITANgd.
- However, the final selection has not yet been made because licensing issues with several candidate algorithms are still being resolved.

**DISCLAIMER:** The contents of this poster are solely the opinions of the author and do not constitute a statement of policy, decision, or position on behalf of the GOES-R Program Office, NOAA, or the U.S. Government.

## References

- Dixon, M., and G. Wiener, 1993: TITAN: Thunderstorm Identification, Tracking, Analysis, and Nowcasting—a radar-based methodology. *J. Atmos. Ocean. Tech.*, **10**, 785-797.
- Joyce, R. J., J. Janowiak, P. A. Arkin, and P. Xie, 2004a: CMORPH: A method that produces global precipitation estimates from passive microwave and infrared data at high spatial and temporal resolution. *J. Hydrometeorol.*, **5**, 487-503.
- , and -----, 2004b: The combination of a passive microwave based satellite rainfall estimation algorithm with an IR based algorithm. Preprints, *13<sup>th</sup> Conf. on Satellite Meteorology and Oceanography*, Norfolk, VA, Amer. Meteor. Soc., CD-ROM, P4.4.
- Kuligowski, R. J., 2002: A self-calibrating GOES rainfall algorithm for short-term rainfall estimates. *J. Hydrometeorol.*, **3**, 112-130.
- Scofield, R. A., R. J. Kuligowski, and J. C. Davenport, 2004: The use of the Hydro-Nowcaster for Mesoscale Convective Systems and the Tropical Rainfall Nowcaster (TRaN) for landfalling tropical systems. Preprints, *Symposium on Planning, Nowcasting, and Forecasting in the Urban Zone*, Seattle, WA Amer. Meteor. Soc., CD-ROM, 1.4.
- Sorooshian, S., K. Hsu, X. Gao, H. V. Gupta, B. Imam, and D. Braithwaite, 2000: Evaluation of PERSIANN system satellite-based estimates of tropical rainfall. *Bull. Amer. Meteor. Soc.*, **81**, 2035-2046.
- Turk, F. J., E. E. Ebert, H. J. Oh, B.-J. Sohn, V. Levizzani, E. A. Smith, and R. Ferraro, 2003: Validation of an Operational Global Precipitation Analysis at Short Time Scales. Preprints, *3<sup>rd</sup> Conf. on Artificial Intelligence*, Long Beach, CA, Amer. Meteor. Soc. CD-ROM, JP1.2.
- Turner, B. J., I. Zawadzki, and U. German, 2004: Predictability of precipitation from continental radar images. Part III: Operational nowcasting implementation (MAPLE). *J. Appl. Meteor.*, **43**, 231-248.